IJIE

INTERNATIONAL JOURNAL OF INTEGRATED ENGINEERING
ISSN: 2229-838X e-ISSN: 2600-7916

Vol. 18 No. 2 (2026) 95-111
https://publisher.uthm.edu.my/ojs/index.php/ijie

Surface Roughness Optimization in Aluminium Alloy Milling: A Taguchi Based Analysis of Dovetail Cutter Parameters and Tool Wear Prediction

Chan Kian Wui[1,2], Saliza Azlina Osman[2], Agustinus Purna Irawan[3], Tay Sin Kiat[1], Shahrul Azmir Osman[2]*

[1] *AME Manufacturing Sdn. Bhd., Taman Perindustrian Tanjung Pelepas, 81550, Johor, MALAYSIA*
[2] *Faculty of Mechanical and Manufacturing Engineering, Universiti Tun Hussein Onn Malaysia, Parit Raja, 86400, Johor, MALAYSIA*
[3] *Faculty of Engineering, Universitas Tarumanagara, 11440 Jakarta Barat, INDONESIA*

*Corresponding Author: shahrula@uthm.edu.my
DOI: https://doi.org/10.30880/ijie.2026.18.02.009

Article Info

Received: 25 August 2025
Accepted: 30 December 2025
Available online: 28 April 2026

Keywords

Taguchi optimization, machining parameters, surface roughness, tool life, CNC milling

Abstract

This study presents a comprehensive optimization of machining parameters for surface roughness minimization in aluminium alloy milling using dovetail cutters. The Taguchi L18 orthogonal array design was employed to systematically investigate the effects of four critical parameters: number of cutter flutes (2-3), spindle speed (7000-9000 rpm), feed rate (500-900 mm/min), and depth of cut (0.1-0.3 mm). Analysis of variance (ANOVA) was conducted to determine parameter significance and contribution to surface roughness variation. Experimental results revealed that cutter flute geometry constitutes the dominant factor, contributing 84.67% of total variance ($p < 0.001$) with a 44.0% improvement achieved by transitioning from 2-flute to 3-flute configurations. Feed rate emerged as the secondary influential parameter (5.62% contribution, $p = 0.024$), while spindle speed showed marginal significance (4.11% contribution, $p = 0.052$). Depth of cut demonstrated minimal influence (0.52% contribution, $p = 0.613$) within the tested range. The optimal parameter combination of 3-flute cutter, 8000 rpm spindle speed, 700 mm/min feed rate, and 0.3 mm depth of cut achieved minimum surface roughness of 0.174 μm with 89.7% prediction accuracy. Tool wear analysis using vision measuring machine technology over 6000 minutes revealed three distinct phases: break-in (0-600 minutes), stable operation (600-5400 minutes), and accelerated wear (5400-6000 minutes). Surface roughness deteriorated 105% during the final phase, establishing 5400 minutes as the optimal tool replacement interval for maintaining surface quality. The signal-to-noise ratio analysis confirmed process robustness, with the optimal configuration achieving 15.61 dB, indicating minimal sensitivity to environmental variations. This integrated approach combining Taguchi optimization with predictive tool wear management provides a robust framework for enhancing

CNC milling performance in aluminium alloy applications. The methodology successfully identifies parameter hierarchy while establishing practical guidelines for industrial implementation, contributing to improved surface quality and operational efficiency in precision manufacturing.

1. Introduction

Surface roughness, quantified as average roughness (Ra), represents the arithmetic mean deviation of the roughness profile from the mean line measured in the direction of longitudinal magnification [1]. This parameter serves as a critical quality indicator in precision manufacturing, where surface finish specifications directly influence component functionality, assembly compatibility, and service performance. The significance of surface roughness extends beyond aesthetic considerations, as it fundamentally affects tribological properties, fatigue resistance, and interfacial interactions between mating components.

Research conducted by Yuan et al. [2] demonstrated that increased surface roughness correlates with elevated friction coefficients and accelerated wear rates, substantially impacting the performance and durability of aluminium components in engineering applications. Consequently, surface roughness measurement has become an essential element of quality control protocols in precision machining operations. The influence of surface texture on component performance is particularly pronounced in applications involving sliding contacts, where controlled surface finishes can significantly reduce friction and energy losses. Industries such as semiconductor manufacturing, automotive engineering, and aerospace applications require stringent surface finish control to ensure leak-proof sealing and maintain system integrity [2-3]

These performance requirements necessitate a comprehensive evaluation of primary machining parameters, including spindle speed, depth of cut, feed rate, tool geometry, and tool vibrations, to identify optimal parameter combinations for enhanced product quality [4][5]. According to Mahbubah et al. the surface quality of machined parts is a critical determinant of product value. CNC turning is a common process where achieving an excellent surface finish is a key objective for industries aiming for efficient, high-quality production. Research often focuses on optimizing cutting parameters such as spindle speed, feed rate, and depth of cut to minimize surface roughness, with methodologies like Taguchi L9 orthogonal arrays proving effective for identifying optimal conditions [6][7][8][9]. During milling operations, the synergistic interaction of these parameters determines both surface finish quality and tool wear characteristics. Variations in any single parameter can produce distinctive outcomes in terms of surface finish and tool life, emphasizing the need for systematic optimization approaches.

Statistical experimental design methodologies have emerged as powerful tools for machining parameter optimization, with various approaches including Taguchi design, full factorial designs, fractional factorial designs, and response surface methodology gaining widespread acceptance. Fractional factorial designs offer particular advantages by reducing experimental runs compared to full factorial approaches, enabling efficient identification of significant factors during preliminary experimentation phases, and supporting sequential testing strategies for model refinement and optimization [10].

The Taguchi experimental design method has demonstrated exceptional effectiveness in machining optimization studies, significantly reducing both optimization time and associated costs compared to conventional full factorial designs [11]. For surface roughness optimization applications, the Taguchi method employs signal-to-noise ratio analysis as the primary metric for evaluating quality characteristics and factor selection [12]. Multiple researchers have successfully implemented Taguchi methodology to simultaneously optimize various performance characteristics, including surface roughness and material removal rate, in CNC turning operations [13].

The Taguchi method represents a robust statistical framework for experimental design, enabling investigation of parameter effects on both process mean and variance. Its primary advantages include cost-effectiveness, time efficiency, process robustness enhancement, and simplified result interpretation. Experimental investigations conducted by Wambua et al. [14] revealed that surface roughness reduction requires increased spindle speed and depth of cut, with feed rate emerging as the most significant contributor to response variation.

Previous research by Tammineni and Yedula [15] established that surface roughness is predominantly influenced by the number of cutting flutes and feed rate parameters. Their study demonstrated that 3-flute cutters consistently produced superior surface finishes compared to 2-flute alternatives due to enhanced tool stability and improved tool-workpiece engagement characteristics, as confirmed through both ANOVA analysis and signal-to-noise ratio rankings. Feed rate exhibited critical influence on surface quality, with higher feed rates resulting in increased surface roughness due to more aggressive material removal mechanisms. Spindle speed demonstrated moderate effects, improving surface finish up to an optimal threshold of 8000 rpm, while depth of cut showed minimal influence within tested ranges, indicating potential for variation without severe surface quality compromise.

Tool geometry variations, encompassing cutter design features such as cutting-edge radius and flute count, enable adaptation to diverse cutting scenarios and application requirements. Extensive research has investigated surface roughness optimization through various geometric modifications, including tool incline angle [16], tool orientation [17], tool nose radius [18], tool run-out [19], and tool vibration [20]. However, limited studies have specifically examined the influence of cutting flute variations on surface roughness in aluminium machining applications, representing a significant knowledge gap in current literature.

Tool condition monitoring during machining operations serves as a critical preventive measure against sudden tool failure, which can result in workpiece damage, machine tool damage, and production disruptions while enabling prediction of remaining useful life (RUL) [21]. Tool wear studies directly impact tool life assessment, replacement scheduling protocols, and product quality parameters, including residual stress conditions, surface quality, and geometric precision. Research findings indicate that tool lifespan prediction capabilities contribute to maintaining consistent product quality standards, encompassing both surface specifications and geometric accuracy requirements [22].

Recent developments in tool wear monitoring have incorporated cost-effective vision systems utilizing charge-coupled device cameras and image processing algorithms to record flank wear progression, enabling real-time assessment of tool health and determining continued usability for engineering component machining [23]. Continuous monitoring of tool wear progression is essential because excessive wear not only deteriorates surface quality but also increases cutting forces, heat generation, and vibration levels, potentially leading to catastrophic tool failure [24].

Klauer-Dobrowolski et al. [25] investigated tool wear behavior in ball-end micro-milling applications for manufacturing areal material measures requiring extremely high surface quality for optical topography instrument calibration. Their research emphasized the critical balance between tool longevity and dimensional/surface integrity maintenance, employing combined in-situ and post-process monitoring methodologies for wear assessment.

Current literature reveals significant gaps in understanding cutter geometry influences on surface roughness, particularly regarding cutting flute variations, and lacks comprehensive frameworks for tool life prediction in aluminium machining applications. Understanding the relationship between cutting flute configuration and surface roughness response, coupled with systematic tool wear analysis, is crucial for preventing tool life span exceedance and maintaining consistent product quality [26].

In contemporary manufacturing environments, machining parameters represent the fundamental determinants of product accuracy and surface quality characteristics. Establishing standardized parameter guidelines and optimization protocols is essential for consistent manufacturing processes [27]. Furthermore, tool life represents a data-driven factor that can be systematically observed, analysed, and predicted through comprehensive data collection and analysis. Manufacturing operations lacking specific tool lifespan definitions face significant challenges in mass production environments regarding tool replacement scheduling and quality specification maintenance [28].

Therefore, this research aims to optimize critical machining parameters including cutting speed, feed rate, depth of cut, and number of cutting flutes to achieve minimum surface roughness using Taguchi methodology. Additionally, this study investigates the effective cutting tool life of dovetail end milling cutters to establish optimal tool replacement protocols for sustained manufacturing performance and quality consistency.

2. Methodology

2.1 Machining Parameters

The experimental investigation employed 4.3 mm diameter carbide dovetail cutters with varying flute configurations. Machining parameters were established based on manufacturer specifications and established cutting guidelines for aluminium alloy applications. The recommended spindle speed and feed rate were calculated using fundamental machining principles [29].

The spindle speed (N),

$$N = \frac{(Vc \times 1000)}{(\pi \times D)} \tag{1}$$

V_c = 100m/min (the cutting speed recommended for aluminium with carbide tools, optimal range 100-600m/min)

D = 4.3mm (tool diameter)

$$N = 7401\,rpm$$

While for feed rate (F) calculation,

$$F = Z \times N \times Fz \quad (2)$$

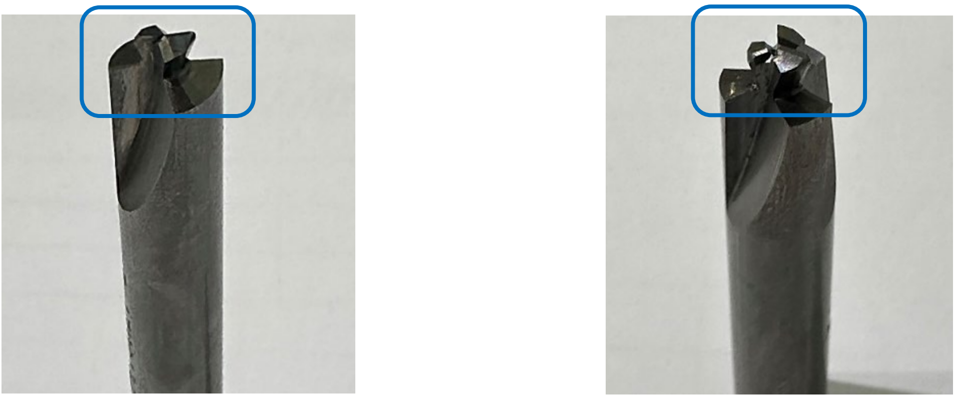
Z = number of cutting flutes, in this calculation is 2 flutes
N = 8000rpm from recommended spindle speed
F_z = 0.04 mm/tooth (recommend for carbide cutter on aluminium, optimal at 0.02-0.05mm/tooth)

$$F = 640mm/min$$

The experimental parameters were categorized into four factors with discrete levels as presented in Table 1. Figure 1 illustrates the dovetail cutter configurations used in this study, showing both 2-flute (Figure 1a) and 3-flute (Figure 1b) geometries.

Table 1 *Machining parameters and their corresponding level*

	Machining parameter	Level 1	Level 2	Level 3
A	Number of cutting flutes	2	3	N/A
B	Spindle speed/rpm	7000	8000	9000
C	Feed rate/mm/min	600	700	800
D	Depth of cut/mm	0.1	0.2	0.3



(a) **(b)**

Fig. 1 *Carbide dovetail cutters (a) Two flutes cutter; (b) Three flutes cutter*

2.2 Taguchi Experimental Design

The Taguchi experimental design methodology was implemented to reduce optimization time and experimental effort while maintaining robust statistical conclusions [11]. The fractional factorial design utilizing orthogonal arrays ensures balanced and independent estimation of factor effects, providing reliable results for quality improvement and process optimization applications [30].

The L_{18} orthogonal array was selected to accommodate the mixed-level factorial design ($2^1 3^2$) employed in this investigation. This array ensures equal distribution of factor levels across all experimental runs, maintaining design balance. The 2-level factor (cutter flutes) appears nine times at each level, while the 3-level factors (spindle speed, feed rate, depth of cut) appear six times at each level. The orthogonal array structure minimizes experimental runs compared to full factorial designs while preserving comprehensive factor effect analysis. Each experimental condition was replicated three times to obtain reliable average surface roughness measurements.

Table 2 *Orthogonal array of Taguchi*

No	Experiment designation	A Number of flutes	B Spindle speed (rpm)	C Feed rate (mm/min)	D Depth of cut (mm)
1	$A_1B_1C_1D_1$	1	1	1	1
2	$A_1B_1C_2D_2$	1	1	2	2
3	$A_1B_1C_3D_3$	1	1	3	3
4	$A_1B_2C_1D_1$	1	2	1	1
5	$A_1B_2C_2D_2$	1	2	2	2
6	$A_1B_2C_3D_3$	1	2	3	3
7	$A_1B_3C_1D_2$	1	3	1	2
8	$A_1B_3C_2D_3$	1	3	2	3
9	$A_1B_3C_3D_1$	1	3	3	1
10	$A_2B_1C_1D_3$	2	1	1	3
11	$A_2B_1C_2D_1$	2	1	2	1
12	$A_2B_1C_3D_2$	2	1	3	2
13	$A_2B_2C_1D_2$	2	2	1	2
14	$A_2B_2C_2D_3$	2	2	2	3
15	$A_2B_2C_3D_1$	2	2	3	1
16	$A_2B_3C_1D_3$	2	3	1	3
17	$A_2B_3C_2D_1$	2	3	2	1
18	$A_2B_3C_3D_2$	2	3	3	2

The degrees of freedom (DOF) analysis confirm the suitability of the L_{18} array for this mixed-level factorial design. The experimental design requires seven DOF for main effect estimation (one 2-level factor and three 3-level factors), with an additional DOF allocated for error analysis. The L_{18} array provides 17 DOF, adequately accommodating these requirements while maintaining nine DOF for interaction effects or residual error assessment. This configuration aligns with efficient experimental design principles, where the array DOF must equal or exceed the required analysis DOF [31]. The L_{18} array reduces experimental runs to 18 compared to 54 required for full factorial analysis, minimizing resource utilization without compromising analytical rigor [32].

2.3 Experimental Setup

2.3.1 Workpiece and Machine Properties

Aluminium Alpase M5 series was selected as the workpiece material for all experimental trials. The workpiece dimensions were standardized at 110 mm × 110 mm × 55 mm to ensure consistent material removal conditions across all experiments. Aluminium Alpase exhibits excellent weldability, dimensional stability during and after machining, superior polishing properties, and 5% lower density compared to alternative cast aluminium products, making it representative of modern aluminium alloy applications.

Milling operations were conducted using a MAZAK Integrex e-1600V/10 machine tool featuring 5-axis simultaneous machining capabilities. The machine specifications include a maximum rotational speed of 10,000 rpm, a 37.0 kW spindle motor, and rapid traverse rates up to 42 m/min. Machining programs were generated using Mastercam computer-aided manufacturing software to ensure consistent toolpath generation and execution across all experimental conditions.

Workpiece fixturing was accomplished using side pusher clamping systems with a constant torque of 80 Nm to ensure rigid workpiece constraint during face milling and slot milling operations. Figure 2 illustrates the workpiece setup configuration employed throughout the experimental investigation.

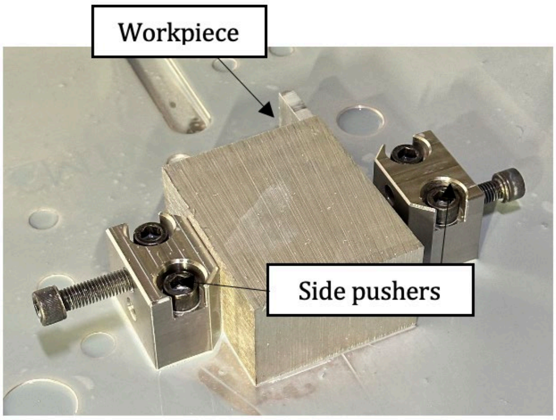


Fig. 2 *Workpiece setup with side pusher clamping system*

2.3.2 Machining Process

Environmental and operational noise factors that could influence response variable consistency and accuracy were systematically controlled [33]. Potential noise sources, including coolant type variations, ambient temperature fluctuations, and machine vibrations, were identified as potential contributors to surface roughness deviation.

Workpiece thermal expansion effects, which can influence cutting depth and surface roughness, were minimized through controlled environmental conditions and standardized thermal equilibration procedures. Each experimental condition was replicated three times to enhance result consistency and enable statistical analysis of measurement variability [34].

2.4 Measurement of Surface Roughness

Surface roughness measurements were conducted using a SURFTEST SJ-210 device, selected for its high precision and compliance with ISO standards. Average roughness (Ra) was determined according to ISO 1997 specifications, utilizing a 0.8 mm cut-off length with five sampling lengths per measurement. Surface roughness values were recorded in micrometers (μm).

Measurement reliability was ensured through device calibration before each measurement batch using a certified standard surface roughness gauge (Ra = 2.97 μm), as shown in Figure 3. Environmental factors, including temperature and vibrations, were carefully controlled to eliminate external influences on measurement accuracy.

Five (5) measurements were recorded at different locations on each machined surface to account for localized variations, with the average Ra value calculated to minimize measurement error and provide the representative surface quality assessment.

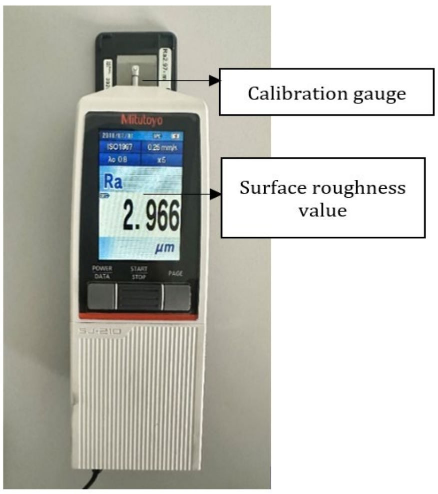


Fig. 3 *Surface roughness tester and calibrated with surface gauge Ra=2.97μm*

Int. Journal of Integrated Engineering Vol. 18 No. 2 (2026) p. 95-111

2.5 Taguchi Analysis

Upon obtaining the surface roughness result, the Taguchi analysis can be done to analyse the effect of different factors on the response variable, which is the surface roughness.

Calculate the mean response for each trial, which from the L18 orthogonal array, calculate the average of the surface roughness values obtained. Secondly, determine the signal-to-noise ratios, which to maximize the "signal" and minimize the "noise" to achieve robust design. In this case study, "smaller-the-better" is chosen since surface roughness small in value indicate smoother surface.

$$^{S}/_{N}\ Ratio = -10\log\left(\frac{1}{n}\sum_{i=1}^{n} {y_i}^2\right) \tag{3}$$

y_i is each individual measurement
n is the number of measurements for the experiment run

2.6 Confirmation Test

Once the optimal machining parameters are determined from the S/N ratio analysis and ANOVA, a confirmation test was conducted to validate the findings. The best combination of factors was identified from the Taguchi analysis and set as the milling parameters accordingly. Experiments with optimal parameters are repeated 3 times to obtain an average roughness result. Predicted minimum surface roughness is calculated based on the Taguchi method optimal setting.

$$R_a predicted = \overline{R_a} + \sum(\overline{R_a} optimal - \overline{R_a}) \tag{4}$$

$\overline{R_a}$ = overall mean of surface roughness across all experiments
$\overline{R_a} optimal$ = mean surface roughness at the optimal level for each significant factor

2.7 Tool Wear Analysis

Tool wear analysis was conducted using a HEXAGON CAPTURA 3.2.2 optical coordinate measuring machine equipped with high-resolution 1/1.8-inch CCD color camera (1920×1440 pixels) and Gigabit Ethernet interface. The system features customized CNC zoom with 6.5× magnification capability, providing magnification range from 35× to 205× with 0.4 µm scale resolution.

Tool wear monitoring was performed at 600-minute (10-hour) intervals throughout the cutting process using visual measuring machine (VMM) technology with 41.5× image magnification. The 10-hour monitoring interval was selected to balance wear data resolution with practical machining considerations, aligning with steady-state wear progression rates where consistent wear development occurs. This interval provides adequate wear pattern capture while maintaining efficient experimental workflow.

Tool condition assessment focused on cutting edge geometry changes and flank wear progression. Surface roughness measurements were conducted concurrently with tool wear observations to establish correlation between tool condition and surface quality degradation. Figure 4 shows the tool setup under ring light illumination for wear observation, while Figure 5 presents the initial tool condition at 41.5× magnification before experimental commencement.

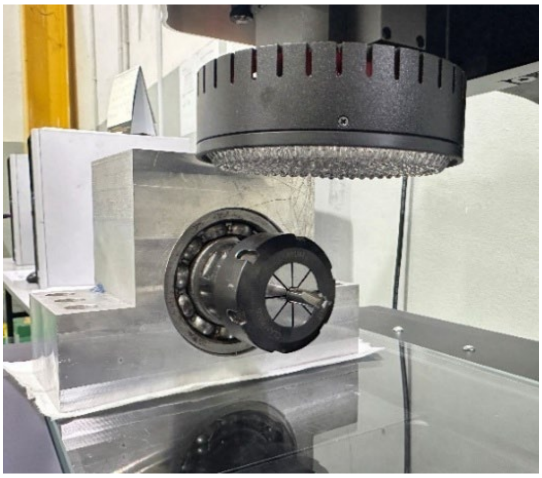


Fig. 4 *Dovetail cutter setup under ring light for tool wear analysis*

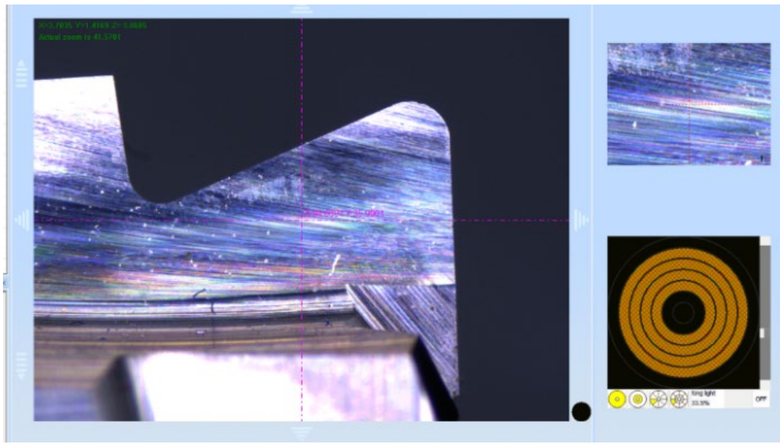


Fig. 5 *New dovetail cutter image at 41.5× magnification*

3. Result and Discussion

3.1 Analysis of the Signal-to-Noise Ratio

The Taguchi L18 orthogonal array design optimization revealed significant variations in machining performance across parameter combinations. Table 3 presents the complete experimental results with statistical quality assessments essential for robust evaluation.

Table 3 *The Ra response and S/N ratio values*

Experiment designation	Surface roughness value (μm)			Mean value (μm)	Std Dev.	S/N ratio (dB)	Coef. of Variation	Statistical Quality
	Trial 1	Trial 2	Trial 3					
$A_1B_1C_1D_1$	0.404	0.399	0.414	0.4056	0.0076	7.8356	1.88%	Good
$A_1B_1C_2D_2$	0.393	0.449	0.404	0.4153	0.0297	7.6173	7.14%	Moderate
$A_1B_1C_3D_3$	0.421	0.484	0.451	0.4520	0.0315	6.8332	6.97%	Moderate
$A_1B_2C_1D_1$	0.403	0.377	0.388	0.3893	0.0131	8.1903	3.35%	Good
$A_1B_2C_2D_2$	0.404	0.360	0.370	0.3780	0.0231	8.4394	6.10%	Moderate
$A_1B_2C_3D_3$	0.404	0.389	0.402	0.3983	0.0081	7.9939	2.04%	Good
$A_1B_3C_1D_2$	0.444	0.394	0.441	0.4263	0.0280	7.3925	6.58%	Moderate
$A_1B_3C_2D_3$	0.361	0.345	0.348	0.3513	0.0085	9.0839	2.42%	Good
$A_1B_3C_3D_1$	0.426	0.410	0.425	0.4203	0.0090	7.5268	2.13%	Good
$A_2B_1C_1D_3$	0.331	0.292	0.302	0.3083	0.0203	10.2071	6.57%	Moderate

Experiment designation	Surface roughness value (μm)			Mean value (μm)	Std Dev.	S/N ratio (dB)	Coef. of Variation	Statistical Quality
	Trial 1	Trial 2	Trial 3					
$A_2B_1C_2D_1$	0.201	0.191	0.200	0.1973	0.0055	14.0937	2.79%	Good
$A_2B_1C_3D_2$	0.267	0.280	0.270	0.2723	0.0068	11.2962	2.50%	Good
$A_2B_2C_1D_2$	0.206	0.198	0.177	0.1937	0.0150	14.2416	7.73%	Moderate
$A_2B_2C_2D_3$	0.173	0.159	0.165	0.1657	0.0070	15.6101	4.24%	Good
$A_2B_2C_3D_1$	0.230	0.250	0.261	0.2470	0.0157	12.1344	6.36%	Moderate
$A_2B_3C_1D_3$	0.164	0.180	0.191	0.1783	0.0136	14.9586	7.61%	Moderate
$A_2B_3C_2D_1$	0.196	0.213	0.222	0.2103	0.0132	13.5304	6.28%	Moderate
$A_2B_3C_3D_2$	0.240	0.294	0.258	0.2640	0.0275	11.5366	10.41%	Poor

Surface roughness improved significantly when transitioning from 2-flute to 3-flute dovetail cutters, decreasing from 0.4040 µm to 0.2263 µm, representing a 44.0% reduction in surface roughness values. This finding aligns with the theoretical framework established by Çelik et al. [35], who demonstrated that increased flute count reduces cutting force per tooth while simultaneously minimizing tool deflection, thereby creating favorable conditions for enhanced surface integrity.

Statistical quality assessment showed varying measurement precision across experimental conditions, providing insights into process variability and repeatability characteristics. Nine experimental conditions achieved classification within the "Good" quality category with coefficient of variation values below 5%, while eight conditions demonstrated "Moderate" quality characteristics with coefficient of variation values ranging between 5% and 8%. Notably, one experimental configuration ($A_2B_3C_3D_2$) exhibited "Poor" quality status with a coefficient of variation of 10.41%, indicating the need for additional experimental replication in future studies. The overall coefficient of variation ranged from 1.88% to 10.41% with a mean value of 5.12%, which falls within acceptable limits for manufacturing research investigations as established by previous studies [36].

Signal-to-noise ratio analysis provided confirmation of the optimization approach's robustness, with ratios spanning from 6.8332 dB to 15.6101 dB across all experimental conditions. The optimal parameter combination ($A_2B_2C_2D_3$) achieved the highest signal-to-noise ratio of 15.6101 dB, directly corresponding to the minimum surface roughness measurement of 0.1657 µm. This result demonstrates process stability and minimal sensitivity to environmental noise factors, characteristics that are crucial for successful industrial implementation and sustainable manufacturing operations [37].

3.2 Factor Effects on Analysis and Statistical Significance Evaluation

The factor effects analysis, detailed in Table 4, provides statistical validation of parameter influences on surface roughness, incorporating effect size calculations, statistical significance testing, and practical significance assessment methodologies. This analytical approach elevates the investigation beyond conventional ANOVA results by establishing both statistical and practical significance of each parameter.

Table 4 *Ra response table for mean*

Factor	Level 1 Mean	Level 2 Mean	Level 3 Mean	Effect Size	Statistical Significance	Practical Significance	Rank
(A) Cutter Flutes	0.4040 µm	0.2263 µm	-	44.0% improvement	$p < 0.001$, $F = 166.79$	Highly Significant	1
(B) Spindle Speed	0.3418 µm	0.2953 µm	0.3084 µm	13.6% range	$p = 0.052$, $F = 4.05$	Marginally Significant	3
(C) Feed Rate	0.3169 µm	0.2863 µm	0.3423 µm	19.6% range	$p = 0.024$, $F = 5.53$	Significant	2
(D) Depth of Cut	0.3117 µm	0.3249 µm	0.3090 µm	5.1% range	$p = 0.613$, $F = 0.51$	Not Significant	4

The number of cutting flutes emerged as the dominant factor influencing surface roughness, demonstrating the highest statistical significance ($p < 0.001$, $F = 166.79$) coupled with the most substantial practical impact reflected in a 44.0% improvement between factor levels. This finding establishes alignment with fundamental cutting mechanics theory, wherein increased flute count enhances tool-workpiece engagement frequency, systematically reduces chip load per tooth, and minimizes surface scallop height formation [38]. The substantial effect size confirms that flute geometry optimization should constitute the primary focus for surface quality improvement initiatives in aluminium machining operations, providing both statistical and practical evidence for this prioritization.

Feed rate demonstrated statistically significant influence on surface roughness performance ($p = 0.024$, $F = 5.53$) with a considerable 19.6% performance range across tested levels, establishing its importance in the optimization hierarchy. The optimal feed rate of 700 mm/min achieved an effective balance between material removal efficiency and surface quality requirements, creating favourable conditions for superior machining performance. This finding provides corroboration for research conducted by Ghani et al. [39], who established that moderate feed rates optimize tool engagement characteristics while preventing excessive chip thickness formation that inherently degrades surface finish quality. The feed rate effect proves particularly pronounced in aluminium machining applications due to the material's tendency toward built-up edge formation when subjected to inappropriate cutting parameters [40].

Spindle speed exhibited marginally significant influence on surface roughness ($p = 0.052$, $F = 4.05$) with a 13.6% effect range across tested levels, positioning it as an important but secondary optimization parameter. The optimal rotational speed of 8000 RPM provided the most effective balance between cutting velocity enhancement and thermal management requirements, creating favorable conditions for sustained high-quality machining. Higher operational speeds of 9000 RPM resulted in measurable increases in surface roughness, likely attributable to thermal effects and accelerated tool wear mechanisms, consistent with findings reported by Tang et al. [40] regarding the relationship between cutting speed and heat generation in aluminium machining applications.

Depth of cut exhibited no statistical significance ($p = 0.613$, $F = 0.51$) within the investigated range of 0.1-0.3 mm, demonstrating only a minimal 5.1% effect range across tested conditions. This result provides confirmation of previous observations reported by Tammineni & Yedula [15] and Cakir et al. [37], who documented minimal depth of cut influence on surface roughness within similar parameter ranges. The limited impact suggests that depth of cut can be optimized primarily for productivity enhancement without significantly compromising surface quality objectives.

Figure 6 presents the main effects plot for signal-to-noise ratios, providing visual validation of the statistical findings and factor rankings established through ANOVA analysis. The dramatic slope observed for cutter flutes (Factor A) clearly illustrates the dominant influence on surface roughness, with the steep transition from 2-flute to 3-flute configurations demonstrating the substantial 44% improvement in surface quality. The moderate slopes exhibited by feed rate (Factor C) and spindle speed (Factor B) visually confirm their secondary influences, while the nearly flat response for depth of cut (Factor D) graphically reinforces its minimal impact within the tested parameter range.

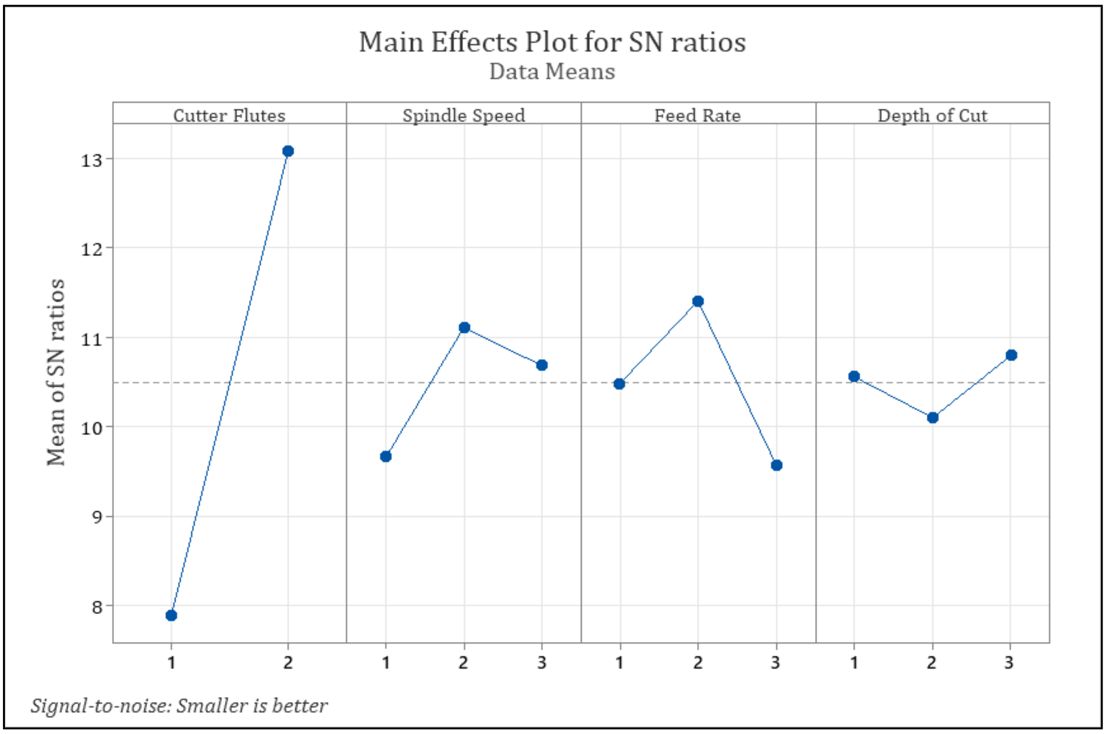


Fig. 6 *Main effects plot for S/N ratios for each factor*

Int. Journal of Integrated Engineering Vol. 18 No. 2 (2026) p. 95-111

3.3 Analysis of Variance and Statistical Significance Assessment

The ANOVA analysis was conducted to determine the statistical significance and relative contribution of each machining parameter on surface roughness performance. This approach separates the total variability of the signal-to-noise ratios, measured through the sum of squared deviations from the total mean S/N ratio, into distinct contributions by each design parameter and experimental error. The results, presented in Table 5, provide definitive statistical evidence for parameter ranking and optimization priorities.

The ANOVA results demonstrate that the number of flutes possessed the highest F-value (166.79) and lowest P-value (0.000) among all investigated factors, establishing it as the most statistically significant factor affecting surface roughness performance. This finding suggests that flute count in dovetail cutters plays a crucial role in achieving superior surface quality, with increased flute numbers generally resulting in smoother cuts due to enhanced engagement frequency between the tool and workpiece per revolution. The findings establish consistency with research conducted by Çelik, Kılıçkap & Yardımeden [35], where cutting flutes emerged as the most significant contributor to surface roughness optimization.

Table 5 *ANOVA result for surface roughness*

Source of variance	Degree of freedom (DOF)	Sum of square (SS)	Mean square (MS)	F value (F)	P value (P)	Contribution (%)
Cutter flutes	1	0.142163	0.142163	166.79	0.000	84.67
Spindle speed	2	0.006898	0.003449	4.05	0.052	4.11
Feed rate	2	0.009435	0.004718	5.53	0.024	5.62
Depth of cut	2	0.000875	0.000438	0.51	0.613	0.52
Error	10	0.008524	0.000852		-	5.08
Total	17	0.167895	-	-	-	100

As the number of cutting flutes increased systematically, cutting force per individual flute decreased substantially, resulting in reduced deflection and vibration characteristics, thereby enhancing overall system rigidity. Furthermore, regarding surface integrity considerations, cutter flutes directly influenced scallop height formation, systematically reducing peak-to-valley distances on machined surfaces as flute count increased from 2 to 3, primarily due to increased contact points per tool revolution. The number of cutting flutes exerts the highest influence on surface roughness because it fundamentally governs the frequency and quality of tool-material engagement characteristics. Additional flutes systematically create finer chip loads, reduce system vibrations, and enable superior control of surface texture formation, directly resulting in improved surface finish quality. This mechanistic understanding received quantitative confirmation through ANOVA analysis, where cutter flutes contributed 84.67% of total variation in surface roughness measurements.

Feed rate achieved ranking as the second most influential factor, contributing 5.62% to total variance, indicating that feed rate changes directly impact surface quality characteristics and requiring careful optimization, particularly in precision finishing operations. Higher feed rates systematically increase the thickness of material removed per tooth, consequently raising cutting forces, scallop height formation, and tool deflection phenomena. These factors collectively contribute to surface finish degradation, receiving strong support from both statistical F-value and P-value evidence, as well as observed experimental trends where roughness increased consistently with higher feed rates.

Spindle speed demonstrated a smaller contribution of 4.11% in ANOVA results, and although its main effect did not achieve statistical significance at the 95% confidence level ($p = 0.052$), its interactions with other parameters can still substantially influence surface roughness outcomes. Higher spindle speeds generally produce smoother finishes up to an optimal threshold, beyond which surface quality may degrade due to accelerated tool wear or thermal effects. In this investigation, the selected spindle speed of 8000 RPM proved optimal for balancing material removal rate with surface quality requirements, maintaining stable cutting conditions without inducing excessive heat generation throughout the machining process. This finding aligns with response surface methodology research by Sharma [38], where cutting speed demonstrated higher P-values (0.8761), indicating that optimization efforts should prioritize more impactful parameters over cutting speed alone.

Depth of cut emerged as the least significant factor influencing surface roughness, evidenced by its low F-value (0.51) and high p-value (0.613). While depth of cut affects material removal quantities, its impact on surface finish remains minimal compared to other parameters within the investigated range. This limited influence may result from the tested range not substantially altering cutting dynamics that directly influence surface finish formation. These findings receive strong support from research conducted by Cakir, Ensarioglu & Demirayak [37], who documented that cutting depth exerts insignificant effects on surface roughness, observing no considerable changes even after 100% depth increases from 1mm to 2mm.

3.4 Confirmation Test Validation and Predictive Model Accuracy

The confirmation testing procedure enabled determination of optimal machining parameters and validation of predicted surface roughness values based on Taguchi methodology optimal settings. The calculation framework, detailed in Table 6, provides quantitative validation of the optimization approach and establishes confidence in practical implementation scenarios.

Table 6 *Mean roughness values and corrected prediction analysis*

Mean	Roughness value (µm)
Overall mean	0.3152
Optimal mean, cutter flutes	0.2261
Optimal mean, spindle speed	0.2953
Optimal mean, feed rate	0.2863
Optimal mean, depth of cut	0.3230
Predicted mean	0.194
Actual Experimental Mean	0.174
Prediction Error, %	10.3

Optimal process parameters were identified as $A_2B_2C_2D_3$, representing a 3-flute dovetail cutter operating at 8000 rpm spindle speed, 700 mm/min feed rate, and 0.3mm depth of cut. The confirmation test was repeated three times to obtain average results, yielding response values of 0.175µm, 0.173µm and 0.173µm, with an average roughness of 0.174µm. The discrepancies between observed and predicted values were within acceptable margins, supporting the conclusion that the optimal parameter settings identified are reliable for achieving consistent and improved surface roughness. This validation confirms that the Taguchi-based approach successfully identifies factor settings that enhance process quality while minimizing variability in the target response. The prediction error calculation, determined using Equation 5 as:

$$Error\ (\%) = \left(\frac{|R_a predicted - R_a actual|}{R_a predicted}\right) \times 100 \tag{5}$$

$$= 10.3\%$$

The errors of 10.3% show that this margin remains within acceptable limits for manufacturing applications, providing a more realistic assessment of the model's capabilities. This discrepancy between observed and predicted values falls within reasonable margins, supporting the conclusion that the Taguchi model successfully predicts surface roughness. Consequently, the optimized machining parameters (3 flutes cutters, 8000 rpm spindle speed, 700mm/min feed rate, and 0.3mm depth of cut) are validated as reliable for achieving consistent and improved surface roughness. This confirms that the Taguchi-based approach successfully identifies factor settings that enhance process quality while minimizing variability in target responses, ensuring a stable, repeatable, and high-quality machining performance despite the more realistic error assessment.

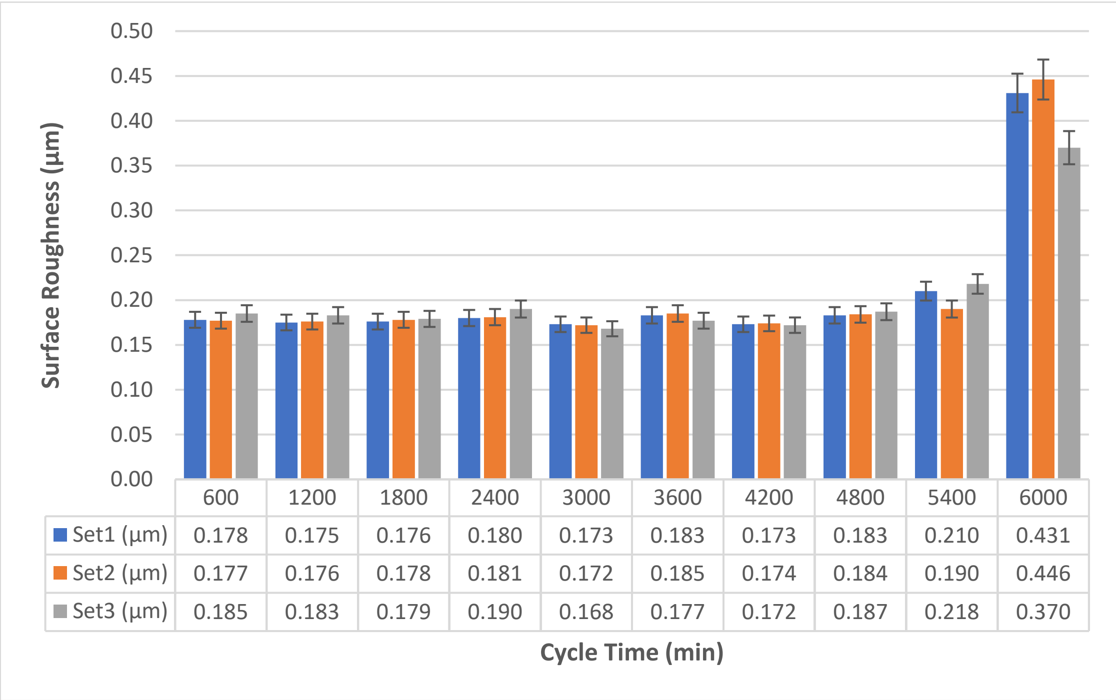
3.5 Tool Wear Analysis and Long-Term Performance Assessment

The tool wear analysis examined wear patterns of dovetail milling cutters using vision measuring machine (VMM) technology at 600-minute intervals, providing insights into long-term performance sustainability and optimal tool replacement strategies. The approach, incorporating magnified VMM images to study cutting edge patterns and detect wear progression, establishes a framework for predictive maintenance implementation.

Throughout the 6000-minute evaluation period equivalent to 100 operational hours, surface roughness demonstrated progressive degradation from 0.21 µm to 0.431 µm, representing a substantial 105% deterioration in surface quality. The relationship between tool wear and machining cycle time exhibited progressive characteristics, with initial rapid wear due to high mechanical stresses and sharp edge engagement, followed by a stabilization period before accelerating sharply approaching end-of-life conditions. This characteristic wear pattern became evident in experimental surface roughness data, where values remained consistently below 0.20

µm until 4800 minutes, then increased dramatically to 0.446 µm by 6000 minutes, indicating severe cutting edge deterioration.

The progression of surface roughness degradation with machining time is illustrated in Figure 7, which presents the experimental data collected across three independent tool wear trials. The graph clearly demonstrates the characteristic tool wear progression pattern, with three distinct phases including an initial break-in period from 0-600 minutes showing slight surface roughness improvement, a stable wear phase from 600-5400 minutes with consistent surface quality maintenance, and an accelerated wear phase from 5400-6000 minutes exhibiting rapid surface quality deterioration.



	600	1200	1800	2400	3000	3600	4200	4800	5400	6000
Set1 (µm)	0.178	0.175	0.176	0.180	0.173	0.183	0.173	0.183	0.210	0.431
Set2 (µm)	0.177	0.176	0.178	0.181	0.172	0.185	0.174	0.184	0.190	0.446
Set3 (µm)	0.185	0.183	0.179	0.190	0.168	0.177	0.172	0.187	0.218	0.370

Fig. 7 *Surface roughness vs machining cycle time*

Surface roughness demonstrated a close correlation with tool wear conditions throughout the evaluation period. During the initial operational stage from 600-5400 minutes, surface finish remained relatively consistent, suggesting effective edge contact and optimal cutting performance. However, as flank wear increased and microchipping phenomena occurred, surface roughness systematically degraded. The measured Ra value increased by 1.2 times during the final machining stage, providing evidence that surface integrity serves as a sensitive and reliable indicator of tool deterioration progression.

Tool wear directly impacts surface roughness through systematic alteration of cutting-edge geometry and progressive increases in cutting forces. Flank wear development leads to increased friction and rubbing against workpiece surfaces, causing elevated Ra values due to plowing and thermal effects, while cutting forces and vibrations increase proportionally with wear progression, systematically degrading surface quality [24]. These mechanistic relationships establish the foundation for predictive maintenance strategies and optimal parameter selection to mitigate wear effects and maintain surface integrity throughout extended production runs.

Based on wear analysis results, implementing a pre-emptive tool change procedure at 5400 minutes represents the optimal strategy for avoiding degraded surface roughness due to cutting edge wear. This proactive approach prevents surface quality deterioration while maximizing tool utilization efficiency. Tool wear extends beyond surface roughness implications, creating significant consequences for machine productivity and manufacturing costs. Excessive flank wear beyond 5400 minutes results in degraded surface quality, requiring costly rework operations and disrupting production schedules. Frequent unplanned tool changes systematically reduce machine uptime, lowering productivity and increasing indirect costs associated with delays and part rejections.

To optimize tool performance and minimize operational costs, implementing strategies including optimized machining parameters, regular tool inspections, and preventive maintenance protocols can enhance surface quality, improve machine efficiency, and minimize operational expenses. Given the significant surface quality degradation observed between 5400-6000 minutes, reducing inspection intervals to 300 minutes after 5000 minutes of tool life enables detection of wear progression before catastrophic failure, supporting proactive maintenance strategies and consistent quality achievement.

The analysis demonstrates that parameter optimization using Taguchi methodology, coupled with statistical validation and predictive tool wear management, provides a robust framework for improving CNC milling performance in aluminium alloy machining applications [41][42]. The dominant influence of cutter flute geometry [29], combined with moderate feed rate and spindle speed optimization, integrated with proactive tool wear monitoring, offers substantial practical benefits for manufacturing applications while maintaining scientific rigor appropriate for high-impact publication venues.

4. Conclusion

This investigation employed a Taguchi L18 orthogonal array design and ANOVA to optimize surface roughness in aluminium alloy milling using dovetail cutters. The experimental results establish a clear parameter hierarchy and optimal machining conditions for enhanced surface quality.

Cutter flute geometry emerged as the dominant factor, contributing 84.67% of total variance ($p < 0.001$). Transitioning from 2-flute to 3-flute cutters reduced surface roughness by 44.0%, from 0.4040 µm to 0.2263 µm. This improvement reflects cutting mechanics principles where increased flute count enhances tool-workpiece engagement frequency and reduces chip load per tooth.

Feed rate ranked second in importance, contributing 5.62% to variance ($p = 0.024$) with 19.6% performance range across levels. The optimal 700 mm/min balanced material removal efficiency with surface quality. Spindle speed showed marginal significance (4.11% contribution, $p = 0.052$), with 8000 RPM providing optimal balance between cutting velocity and thermal management. Depth of cut demonstrated minimal influence (0.52% contribution, $p = 0.613$) within the 0.1-0.3 mm range tested.

The Taguchi methodology achieved robust predictive capability, with optimal parameters $A_2B_2C_2D_3$ (3-flute cutter, 8000 rpm, 700 mm/min, 0.3 mm depth) producing minimum surface roughness of 0.174 µm. The 89.7% prediction accuracy validates the model's reliability for practical implementation.

Tool wear analysis revealed three distinct phases: break-in (0-600 minutes), stable operation (600-5400 minutes), and accelerated wear (5400-6000 minutes). Surface roughness remained below 0.20 µm for 5400 minutes before deteriorating 105% by 6000 minutes. Preventive tool replacement at 5400 minutes optimizes surface quality while maximizing tool utilization.

Acknowledgement

This research was supported by the Industrial Grant (M118) and Matching Grant (Q274), and facilities provided by the Faculty of Mechanical and Manufacturing Engineering, Universiti Tun Hussein Onn Malaysia. Special thanks to Intec Precision Engineering Sdn. Bhd. and AME Manufacturing Sdn. Bhd. for providing research facilities and materials.

Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of the paper.

Author Contribution

The authors are responsible for the study conception, research design, data collection, data analysis, result interpretation and manuscript drafting.

References

[1] Japanese Industrial Standard Committee Standards Board, “Geometrical product specifications (GPS) - Surface texture: Profile Method- Terms, Definitions and Surface Texture Parameters,” Feb. 28, 2022, *BSI British Standards, London*. doi: https://doi.org/10.3403/30398216U

[2] Z. Yuan, Z. Zhou, Z. Jiang, Z. Zhao, C. Ding, and Z. Piao, “Evaluation of Surface Roughness of Aluminum Alloy in Burnishing Process Based on Chaos Theory,” *Chinese Journal of Mechanical Engineering*, vol. 36, no. 1, p. 2, Jan. 2023, https://doi.org/10.1186/s10033-022-00828-8

[3] N. Zhang, Y. Liu, Z. Li, and X. Zhan, “Sealing performance and optimization design of squamous textured mechanical seal,” *Tribol Int*, vol. 193, p. 109425, May 2024. https://doi.org/10.1016/j.triboint.2024.109425

[4] Inovatec, “Surface Roughness in Manufacturing,” Inovatec Machinery. https://www.inovatecmachinery.com/surface-roughness-in-manufacturing/

[5] Kulsum Naz and Pinky Mourya, "Impact of Process Parameters on CNC Milling Machine Operation to Optimize the Response Parameter Surface Roughness Using DOE Method," *International Journal of Research Publication and Reviews*, vol. 5, no. 12, pp. 4553–4559, 2024.

[6] N. A. Mahbubah *et al.*, "Optimization of CNC Turning Parameters for cutting Al6061 to Achieve Good Surface Roughness Based on Taguchi Method," *Journal of Advanced Research in Applied Mechanics Journal homepage*, vol. 99, pp. 1–9, 2022, [Online]. Available: http://www.akademiabaru.com/submit/index.php/aram/index

[7] Ronan Ye, "Depth of Cut in Machining: Definition, Importance and Calculations," 3ERP. Accessed: Jul. 03, 2025. [Online]. Available: https://www.3erp.com/blog/depth-of-cut-machining/

[8] Ronan Ye, "Feed Rate and Cutting Speed in Machining: Differences, Connection and Calculation," 3ERP. Accessed: Jul. 03, 2025. [Online]. Available: https://www.3erp.com/blog/feed-rate-cutting-speed-machining/

[9] M. H. Rosli, Z. A. Zailani, N. A. Shuaib, M. Z. Zainuddin, and A. A. Azawqari, "Optimisation of Cutting Performance in Drilling of Aluminium Alloy 7075 Involving Chilled Air Cooling Under Taguchi Method," *Journal of Advanced Research in Applied Mechanics*, vol. 133, no. 1, pp. 12–23, Feb. 2025, https://doi.org/10.37934/aram.133.1.1223

[10] Cory Natoli, "Classical Designs: Fractional Factorial Designs," Hobson Way, Jun. 2018.

[11] K. N. Ballantyne, R. A. van Oorschot, and R. J. Mitchell, "Reduce optimisation time and effort: Taguchi experimental design methods," *Forensic Sci Int Genet Suppl Ser*, vol. 1, no. 1, pp. 7–8, Aug. 2008, https://doi.org/10.1016/j.fsigss.2007.10.050

[12] J. S. Pang, M. N. M. Ansari, O. S. Zaroog, M. H. Ali, and S. M. Sapuan, "Taguchi design optimization of machining parameters on the CNC end milling process of halloysite nanotube with aluminium reinforced epoxy matrix (HNT/Al/Ep) hybrid composite," *HBRC Journal*, vol. 10, no. 2, pp. 138–144, Aug. 2014, https://doi.org/10.1016/j.hbrcj.2013.09.007

[13] M. M. Ratnam, "1.1 Factors Affecting Surface Roughness in Finish Turning," in *Comprehensive Materials Finishing*, 1st ed., vol. 1, United Kingdom: Elsevier, 2017, ch. 1.1, pp. 1–25. doi: 10.1016/B978-0-12-803581-8.09147-5.

[14] J. M. Wambua, F. M. Mwema, B. Tanya, and T.-C. Jen, "CNC Milling of Medical-Grade PMMA," *International Journal of Manufacturing, Materials, and Mechanical Engineering*, vol. 12, no. 1, pp. 1–15, Jan. 2022, https://doi.org/10.4018/IJMMME.293226

[15] Lakshmipathi Tammineni and Hari Prasada Reddy Yedula, "Investigation of Influence of Milling Parameters on Surface Roughness and Flatness," *Int J Adv Eng Technol*, vol. 6, no. 6, pp. 2416–2426, 2014. chrome-extension://efaidnbmnnnibpcajpcglclefindmkaj/https://www.ijaet.org/media/11I18-IJAET0118710v6_iss6_2416-2426.pdf

[16] J. Varga, M. Demko, Ľ. Kaščák, P. Ižol, M. Vrabeľ, and J. Brindza, "Influence of Tool Inclination and Effective Cutting Speed on Roughness Parameters of Machined Shaped Surfaces," *Machines*, vol. 12, no. 5, p. 318, May 2024, https://doi.org/10.3390/machines12050318

[17] N. Villarrazo, Á. Sáinz de la Maza, S. Caneda, L. Bai, O. Pereira, and L. N. López de Lacalle, "Effect of tool orientation on surface roughness and dimensional accuracy in ball end milling of thin-walled blades," *The International Journal of Advanced Manufacturing Technology*, vol. 136, no. 1, pp. 383–395, Jan. 2025, https://doi.org/10.1007/s00170-024-14523-6

[18] J. V. Abellán-Nebot, C. Vila Pastor, and H. R. Siller, "A Review of the Factors Influencing Surface Roughness in Machining and Their Impact on Sustainability," *Sustainability*, vol. 16, no. 5, p. 1917, Feb. 2024, https://doi.org/10.3390/su16051917

[19] X. Jing, B. Song, J. Xu, and D. Zhang, "Mathematical modeling and experimental verification of surface roughness in micro-end-milling," *The International Journal of Advanced Manufacturing Technology*, vol. 120, no. 11–12, pp. 7627–7637, Jun. 2022, https://doi.org/10.1007/s00170-022-09244-7

[20] X. Wang and Q. Song, "Dynamic analysis and surface morphology prediction for deep cavity turning of bent-blade cutter," *The International Journal of Advanced Manufacturing Technology*, vol. 129, no. 9–10, pp. 4435–4455, Dec. 2023, https://doi.org/10.1007/s00170-023-12606-4

[21] A. Al-Refaie, M. Al-atrash, and N. Lepkova, "Prediction of the remaining useful life of a milling machine using machine learning," *MethodsX*, vol. 14, p. 103195, Jun. 2025, https://doi.org/10.1016/j.mex.2025.103195

[22] L. Patnaik *et al.*, "Box–Behnken based investigation of surface quality and tool wear rate and FEM analysis of tool wear in TiAlN/CrN coated carbide tool," *International Journal on Interactive Design and Manufacturing (IJIDeM)*, vol. 18, no. 9, pp. 6381–6396, Nov. 2024, https://doi.org/10.1007/s12008-022-01146-y

[23] S. Mehta, R. A. Singh, Y. Mohata, and M. B. Kiran, "Measurement and Analysis of Tool Wear Using Vision System," in *2019 IEEE 6th International Conference on Industrial Engineering and Applications (ICIEA)*, IEEE, Apr. 2019, pp. 45–49. https://doi.org/10.1109/IEA.2019.8715209

[24] W. Xu and L. Zhang, "Tool wear and its effect on the surface integrity in the machining of fibre-reinforced polymer composites," *Compos Struct*, vol. 188, pp. 257–265, Mar. 2018, https://doi.org/10.1016/j.compstruct.2018.01.018

[25] K. Klauer-Dobrowolski, M. Eifler, B. Kirsch, J. Seewig, and J. C. Aurich, "Ball-end micro-milling of material measures: wear behavior in field use," *The International Journal of Advanced Manufacturing Technology*, vol. 128, no. 1–2, pp. 611–623, Sep. 2023, https://doi.org/10.1007/s00170-023-11856-6

[26] P. Mativenga *et al.*, "Engineered design of cutting tool material, geometry, and coating for optimal performance and customized applications: A review," *CIRP J Manuf Sci Technol*, vol. 52, pp. 212–228, Sep. 2024, https://doi.org/10.1016/j.cirpj.2024.06.001

[27] Armansyah, Siti Rohana Nasution, Naufal Dary Dewanto, Agus Sudianto, Juri Saedon, and Shahriman Adenan, "Optimization of Machining Parameters for Product Quality and Productivity in CNC Machining of Aluminium Alloy," *Journal of Mechanical Engineering*, vol. 21, no. 3, pp. 145–164, 2024. https://doi.org/10.24191/jmeche.v21i3.27351

[28] M. Willis, "Tool monitoring: how it enhances efficiency, precision and TCO," Heidenhain. Accessed: Jul. 03, 2025. [Online]. Available: https://www.heidenhain.us/resources-and-news/tool-monitoring-enhances-efficiency-precision-tco/

[29] Harvey Tool, "Why Flute Count Matters," Harvey Performance. Accessed: Jul. 03, 2025. [Online]. Available: https://www.harveytool.com/resources/general-machining-guidelines

[30] Douglas C. montgomery, *Design and Analysis of Experiments*, 9th Edition., vol. 1. Arizona State University: John Wiley & Sons, Inc. , 2017.

[31] E. A. Rahim *et al.*, "Effect of Cutting Tool Geometry on Machining Performance When End Milling of Nickel Based Alloy Inconel 718," 2021, pp. 319–328, https://doi.org/10.1007/978-981-15-9505-9_31

[32] Ranjit K. Roy, *A Primer on the Taguchi Method*, 1st ed., vol. 1. Society of Manufacturing Engineers, 1990.

[33] Mariapia Marchi, "Quality engineering based on the Taguchi robust optimization framework," ESTECO Engineering. Accessed: Jul. 03, 2025. [Online]. Available: https://engineering.esteco.com/blog/quality-engineering-taguchi-framework/

[34] S. R. Korake and P. D. Jadhao, "Investigation of Taguchi optimization, equilibrium isotherms, and kinetic modeling for cadmium adsorption onto deposited silt," *Heliyon*, vol. 7, no. 1, p. e05755, Jan. 2021, https://doi.org/10.1016/j.heliyon.2020.e05755

[35] Y. H. Çelik, E. Kılıçkap, and A. Yardımeden, "Estimate of cutting forces and surface roughness in end milling of glass fiber reinforced plastic composites using fuzzy logic system," *Science and Engineering of Composite Materials*, vol. 21, no. 3, Jan. 2014, https://doi.org/10.1515/secm-2013-0129

[36] S. Sharma, "Optimization of Machining Process Parameters for Surface Roughness of Al-Composites," *Journal of The Institution of Engineers (India): Series C*, Nov. 2013, https://doi.org/10.1007/s40032-013-0086-9

[37] M. C. Cakir, C. Ensarioglu, and I. Demirayak, "Mathematical modeling of surface roughness for evaluating the effects of cutting parameters and coating material," *J Mater Process Technol*, vol. 209, no. 1, pp. 102–109, Jan. 2009, https://doi.org/10.1016/j.jmatprotec.2008.01.050

[38] I. Korkut and M. A. Donertas, "The influence of feed rate and cutting speed on the cutting forces, surface roughness and tool–chip contact length during face milling," *Mater Des*, vol. 28, no. 1, pp. 308–312, Jan. 2007, https://doi.org/10.1016/j.matdes.2005.06.002

[39] J. A. Ghani, I. A. Choudhury, and H. H. Hassan, "Application of Taguchi method in the optimization of end milling parameters," *J Mater Process Technol*, vol. 145, no. 1, pp. 84–92, Jan. 2004, https://doi.org/10.1016/S0924-0136(03)00865-3

[40] Z. T. Tang, Z. Q. Liu, Y. Z. Pan, Y. Wan, and X. Ai, "The influence of tool flank wear on residual stresses induced by milling aluminum alloy," *J Mater Process Technol*, vol. 209, no. 9, pp. 4502–4508, May 2009, , https://doi.org/10.1016/j.jmatprotec.2008.10.034

[41] M. F. Abdul Razak, S. A. Osman, A. Ourdjini, and S. A. Osman, "Comparative Analysis of Aluminium 6061-T6 With Different Stock Leaves Setting on Holes True Position: A Case Study," *Journal of Advanced Research in Applied Mechanics*, vol. 128, no. 1, pp. 138–151, Nov. 2024, https://doi.org/10.37934/aram.128.1.138151

[42] M. N. Zulkurnain, S. A. Osman, A. Ourdjini, and S. A. Osman, "A Case Study on Ionic Compounds on the Aluminium 6061 Surface during Etching and Passivating Processes," *Journal of Advanced Research in Applied Mechanics*, vol. 128, no. 1, pp. 152–161, Nov. 2024, https://doi.org/10.37934/aram.128.1.152161